

Behavioral Economics

Topic 1: Choice under Uncertainty
Lecture 2: The Standard Model —
Expected Utility

Professor Bushong



Taking Stock



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- Introduction to the course and material
- Any questions after reading the syllabus?

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Logistics:

- Problem Set 0 is posted – optional “background” material on optimization
- Problem Set 1 is posted – the first real problem set; due Tuesday, September 15
 - Tip: start early – don't wait until the last minute

Our Outline



- 1 History of Risk
- 2 Defining the Environment
- 3 Expected Value Theory
- 4 Risk Aversion
- 5 Expected Utility
- 6 CRRA Utility
- 7 Applications of Expected Utility

A Historical Perspective



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Today’s lecture will cover insights from the mid 18th century to modern approaches.

Defining the Environment



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- E.g., if we don't define what it means for someone to “get sick”, it's hard to have productive conversations about appropriate health policy.

This seems to be especially important when we discuss “intuitive” things like “risk”.

- Your task: understand the definitions in this course — they are *precise*.

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Example B: When you buy a new car, you are buying a lottery. For instance, it might be that with probability $1/2$ it will be a car that you love (high value), with probability $2/5$ it will be a car that only adequately serves your needs (low value), and with probability $1/10$ it will be a "lemon" (worthless).

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Example C: More abstractly, you might get x_1 with probability p_1 , x_2 with probability p_2 , and x_3 with probability p_3 (where $p_1 + p_2 + p_3 = 1$).

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- Suppose you face a choice between two lotteries. How do you decide?

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E.g. the expected value of a 50/50 gamble in which you might win \$10 and otherwise win nothing is \$5.

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How much would an expected-value maximizer pay? The “paradox”:

- The *EV* of this bet is ∞ , but people are unwilling to pay much for it. Hence, *EV* is not a good description of people's choices.

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Implication 2: Maximizing utility implies people turn down many risks.

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- Except it's not true all the time . . . we'll discuss this later.

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Could an expected-utility maximizer (EU maximizer) choose
 $(100, \frac{1}{2}; 0, \frac{1}{2})$ over $(100, \frac{1}{2}; 100, \frac{1}{2})$?

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■ And we're left with a pretty unsatisfying theory of behavior.

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Three Comments:

(1) We say that expected-utility theory can “explain” a choice if there exists a utility function $u(x)$ such that an EU maximizer with utility function $u(x)$ would make that choice.

(2) Even when we put no restrictions on the utility function $u(x)$, although an individual choice cannot violate EU, combinations of choices can violate EU.

■ E.g., $(100, \frac{1}{2}; 0, \frac{1}{2}) \succ (200, \frac{1}{2}; 0, \frac{1}{2})$

AND $(100, \frac{1}{3}; 500, \frac{2}{3}) \prec (200, \frac{1}{3}; 500, \frac{2}{3})$

(3) When we put **restrictions** on the utility function $u(x)$, then even an individual choice could violate EU.

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Result: Under EU with “more is better,” a person will never choose a dominated lottery.

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Result: Under expected-utility theory, a person is risk-averse if and only if her utility function is concave ($u''(x) < 0$ — slope is getting flatter as x gets bigger)

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Result: Under expected-utility theory, a person is risk-loving if and only if her utility function is convex ($u''(x) > 0$ — slope is getting steeper as x gets bigger)

Basic Implications of EU



To incorporate risk-aversion (or risk-seeking), we must assume more about the utility function.

Result: Under expected-utility theory, a person is risk-averse if and only if her utility function is concave ($u''(x) < 0$ — slope is getting flatter as x gets bigger)

Result: Under expected-utility theory, a person is risk-neutral if and only if her utility function is linear ($u''(x) = 0$ — slope is constant)

Result: Under expected-utility theory, a person is risk-loving if and only if her utility function is convex ($u''(x) > 0$ — slope is getting steeper as x gets bigger)

Note: In this class, whenever we say that someone is a risk-averse (or risk-neutral or risk-loving) expected-utility maximizer, we'll implicitly assume more is better as well.

Five Features/Issues of Expected Utility



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EU theory says evaluate prospect $\mathbf{x}$ according to:

$$EU(\mathbf{x}; w) \equiv \sum_{i=1}^n p_i u(w + x_i).$$

Example: Demand for Insurance



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or

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- Point: The level of utility doesn't matter, only the comparisons.

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Question: How to formalize "more risk averse"?

Definition: The *coefficient of risk aversion* at wealth w is

$$r(w) = \frac{-u''(w)}{u'(w)}.$$

Suppose w_A is person A 's wealth and w_B is person B 's wealth. If $r(w_A) > r(w_B)$ then person A is less likely than person B to accept a risky gamble.

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Note: A person's risk aversion depends on both her utility function and her wealth.

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How is one's willingness to accept a gamble likely to depend on my wealth?

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- Economists often assume risk aversion decreases with wealth:

$$\uparrow w \implies \downarrow r(w).$$

An Important Functional Form



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Brief Calculus Refresher



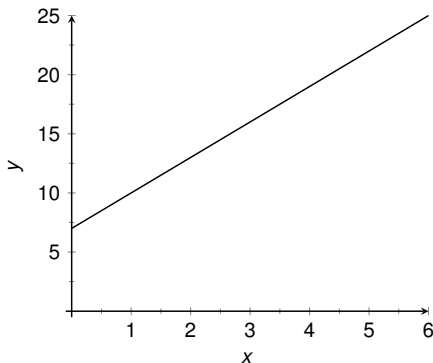
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Slope



- Recall: basic idea of a slope is the **rise** (change in y) over the **run** (change in x)
- For straight lines (linear functions), the slope is the same everywhere:

$$y = f(x) = mx + b \rightarrow m \text{ is the slope}$$

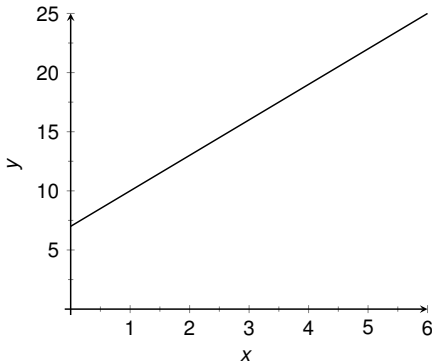


Slope



- For any two points on the graph, the slope of the line between them is

$$\text{Slope} = \frac{\text{rise}}{\text{run}} = \frac{f(x_2) - f(x_1)}{x_2 - x_1}$$

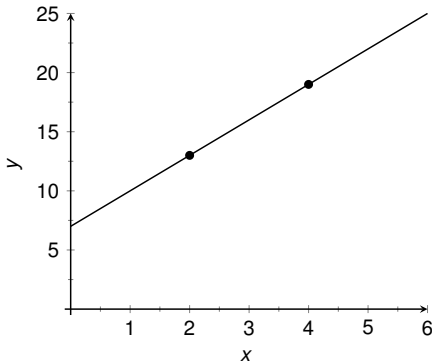


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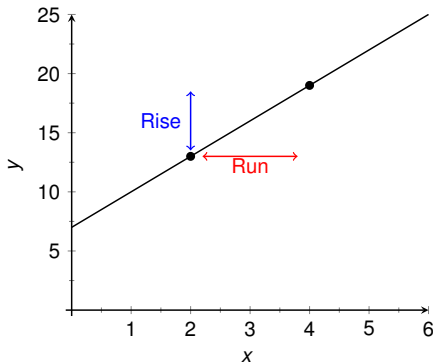


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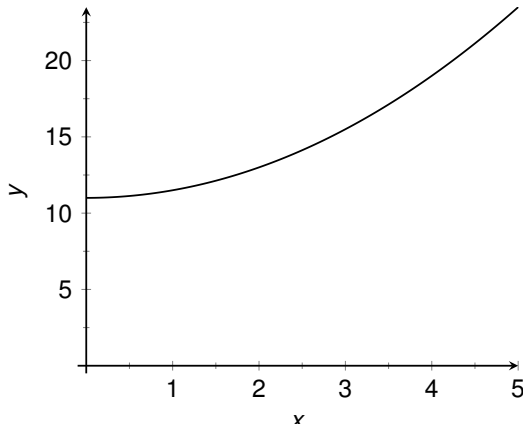
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Slope and Curvature



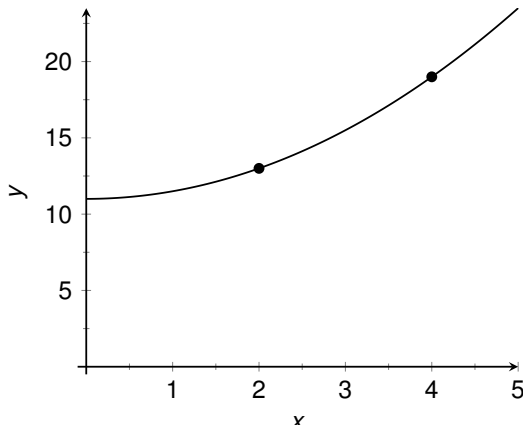
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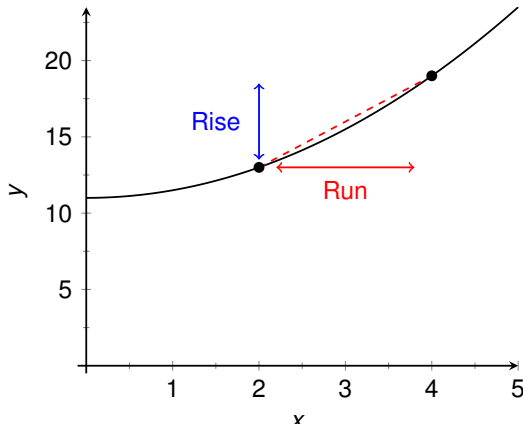
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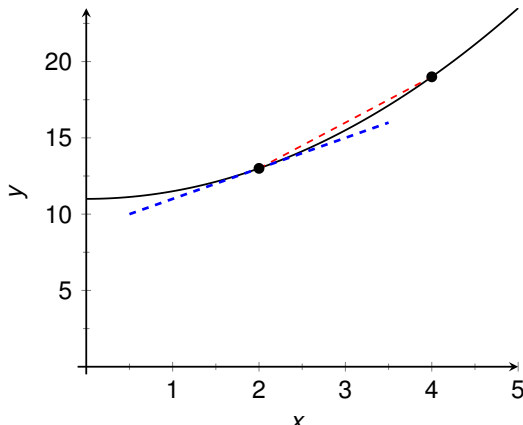
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Slope and Curvature



- If the function is not linear, i.e., it has some **curvature**, taking the slope of a line between two points only *approximates* the slope
- Taking **derivatives** gives us a more precise measure of the slope



- **Idea:** to obtain a more precise approximation of the slope at $x_1 = x$, calculate the slope of the line between $(x_1, f(x_1))$ and $(x_2, f(x_2))$ as x_2 gets arbitrarily close to x_1
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- Note: we can think of a derivative as the “marginal value” of a function
 - It tells us how much y would change if x were to increase by a small amount

Computing Marginal Values of Functions



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- Other way to word this: derivative of f with respect to x , denoted by $\frac{df(x)}{dx}$
- Yet another way to write this: $f'(x)$

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- Why?
- Graphically: the graph of $y = m$ is a horizontal line $\Rightarrow$ it's neither increasing or decreasing $\Rightarrow$ **derivative is zero**

Derivative Rule 1: Constant Functions



- If y is a constant function of x , i.e. $y = b$ (a constant), then

$$\frac{dy}{dx} = 0.$$

- Example: $y = 42 \Rightarrow \frac{dy}{dx} = 0$
- Example: $y = -100 \Rightarrow \frac{dy}{dx} = 0$
- Why?
- Graphically: the graph of $y = m$ is a horizontal line $\Rightarrow$ it's neither increasing or decreasing $\Rightarrow$ **derivative is zero**
- Put differently, if $y = m$, then y doesn't depend on x at all
 - **Thus, a small change in x doesn't change y at all $\Rightarrow$ derivative is zero!**

Derivative Rule 2: Linear Functions (i.e., constant time



- If y is a linear function of x , i.e. $y = mx + b$, then

$$\frac{dy}{dx} = m.$$

Derivative Rule 2: Linear Functions (i.e., constant time)



- If y is a linear function of x , i.e. $y = mx + b$, then

$$\frac{dy}{dx} = m.$$

- Example: $y = 10x + 2 \Rightarrow \frac{dy}{dx} =$

Derivative Rule 2: Linear Functions (i.e., constant time)



- If y is a linear function of x , i.e. $y = mx + b$, then

$$\frac{dy}{dx} = m.$$

- Example: $y = 10x + 2 \Rightarrow \frac{dy}{dx} = 10$

Derivative Rule 2: Linear Functions (i.e., constant time)



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- Example: $y = 10x + 2 \Rightarrow \frac{dy}{dx} = 10$
- Note that the function $y = mx + b$ is just a straight line with slope m
 - b is the y -intercept, which just shifts the graph up and down but doesn't affect its slope

Derivative Rule 2: Linear Functions (i.e., constant time)



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- Example: $y = 10x + 2 \Rightarrow \frac{dy}{dx} = 10$
- Note that the function $y = mx + b$ is just a straight line with slope m
 - b is the y -intercept, which just shifts the graph up and down but doesn't affect its slope
- The fact that dy/dx is a constant means that the slope is never-changing

Derivative Rule 3: Functions that have variable raised to a power



- If y is a power function of x , i.e. $y = ax^n$ where a and n are constants, then

$$\frac{dy}{dx} = anx^{n-1}.$$

Derivative Rule 3: Functions that have variables raised



- If y is a power function of x , i.e. $y = ax^n$ where a and n are constants, then

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- Simple procedure: Multiply the function by its exponent, and then subtract 1 from the original exponent

Derivative Rule 3: Functions that have variable exponents



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- Simple procedure: Multiply the function by its exponent, and then subtract 1 from the original exponent
- Example: $y = 5x^2 \Rightarrow \frac{dy}{dx} =$

Derivative Rule 3: Functions that have variable raised to a power



- If y is a power function of x , i.e. $y = ax^n$ where a and n are constants, then

$$\frac{dy}{dx} = anx^{n-1}.$$

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- Example: $y = 5x^2 \Rightarrow \frac{dy}{dx} = 5 \cdot 2 \cdot x^{2-1} = 10x$

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- Example: $y = 5x^2 \Rightarrow \frac{dy}{dx} = 5 \cdot 2 \cdot x^{2-1} = 10x$
- Practice:
 - $y = 40x^3 \Rightarrow$

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 - $y = \sqrt{x} = x^{\frac{1}{2}} \Rightarrow$

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- Example: $y = 5x^2 \Rightarrow \frac{dy}{dx} = 5 \cdot 2 \cdot x^{2-1} = 10x$
- Practice:
 - $y = 40x^3 \Rightarrow$
 - $y = \sqrt{x} = x^{\frac{1}{2}} \Rightarrow$
 - $y = 5/x^3 = 5x^{-3} \Rightarrow$

Derivative Rule 4: Functions that have sums of variables



- If the overall function is the sum of many functions: Simply split up the function, and take the derivatives of the individual bits. Then add them back together.

Derivative Rule 4: Functions that have sums of variables



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- If $y = f(x) + g(x)$, then

$$\frac{dy}{dx} = \frac{df}{dx} + \frac{dg}{dx}.$$

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- Example: $y = 3x^2 - 7x + 10 \Rightarrow \frac{dy}{dx} =$

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- Practice:

- $y = 9x + 163 \Rightarrow$

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- Practice:

- $y = 9x + 163 \Rightarrow$
- $y = 0.5x^3 + 0.1x^2 - 9 \Rightarrow$
- $y = -40x + 5x^{-2} \Rightarrow$

Derivative Rule 5: Chain Rule (composition of functions)



- If the overall function is the composition of two functions, then take the derivative of the outside function evaluated at the inside one, and multiply by the derivative of the inside.

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- Example: $u(x) = (5 + 2\alpha x)^3 \Rightarrow \frac{du}{dx} =$

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- Example: $u(x) = (5 + 2x)^3 \Rightarrow \frac{du}{dx} = 3(5 + 2x)^2 \cdot (2)$

- Practice:

- $y = \sqrt{3x + x^3} \Rightarrow$

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- $y = \ln(2 + 3x^2) \Rightarrow$

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- $y = \ln(2 + 3x^2) \Rightarrow$

- Note: There are a few other derivative rules worth knowing (product rule, quotient rule, etc.) but we can address those when needed.

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- Practice:

- $y = \sqrt{3x + x^3} \Rightarrow$

- $y = \ln(2 + 3x^2) \Rightarrow$

- Note: There are a few other derivative rules worth knowing (product rule, quotient rule, etc.) but we can address those when needed. **Derivative tables are useful too.**

Unconstrained Maximization



To find x value that maximizes a function:

- 1 Take derivative and find places with slopes equal to 0

Unconstrained Maximization



To find x value that maximizes a function:

- 1 Take derivative and find places with slopes equal to 0
- 2 To tell if these places represent maximums or minimums: determine if function is concave/convex at those places (2nd Derivative Test)

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■ **Example:**

$$f(x) = 6x - x^2 \quad \Rightarrow$$

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$$f(x) = 6x - x^2 \quad \Rightarrow \quad f'(x) = 6 - 2x$$

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- $f'(x)$ is zero at $x =$

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■ **Example:**

$$f(x) = 6x - x^2 \quad \Rightarrow \quad f'(x) = 6 - 2x$$

- $f'(x)$ is zero at $x = 3$

Unconstrained Maximization



To find x value that maximizes a function:

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- 2 To tell if these places represent maximums or minimums: determine if function is concave/convex at those places (2nd Derivative Test)

■ **Example:**

$$f(x) = 6x - x^2 \quad \Rightarrow \quad f'(x) = 6 - 2x$$

- $f'(x)$ is zero at $x = 3$
- But is function maximized at $x = 3$ or minimized?

Unconstrained Maximization



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- $f'(x)$ is zero at $x = 3$
- But is function maximized at $x = 3$ or minimized?
- Second derivative: $f''(x) = -2$

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- $f'(x)$ is zero at $x = 3$
- But is function maximized at $x = 3$ or minimized?
- Second derivative: $f''(x) = -2$
 - If second derivative is positive, then function **convex**
 - If it is negative, function is **concave**

Unconstrained Maximization



To find x value that maximizes a function:

- 1 Take derivative and find places with slopes equal to 0
- 2 To tell if these places represent maximums or minimums: determine if function is concave/convex at those places (2nd Derivative Test)

■ Example:

$$f(x) = 6x - x^2 \quad \Rightarrow \quad f'(x) = 6 - 2x$$

- $f'(x)$ is zero at $x = 3$
- But is function maximized at $x = 3$ or minimized?
- Second derivative: $f''(x) = -2$
 - If second derivative is positive, then function **convex**
 - If it is negative, function is **concave**
- We are in the concave case in this example, and hence **function is maximized at $x = 3$**

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce
- Assumptions:
 - Demand curve: $P = 100 - Q$

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce
- Assumptions:
 - Demand curve: $P = 100 - Q$
 - Cost of producing each unit: $c = 10$

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce
- Assumptions:
 - Demand curve: $P = 100 - Q$
 - Cost of producing each unit: $c = 10$
- Revenue from selling Q units: $Q \cdot P = Q \cdot (100 - Q)$

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce
- Assumptions:
 - Demand curve: $P = 100 - Q$
 - Cost of producing each unit: $c = 10$
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- Cost from producing Q units: $10 \times Q$

Unconstrained Maximization: Example



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- Cost from producing Q units: $10 \times Q$
 - ⇒ Profit = Revenue – Costs

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 - ⇒ Profit = Revenue – Costs ⇒ $\pi = Q(100 - Q) - 10Q$

Unconstrained Maximization: Example



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 - Demand curve: $P = 100 - Q$
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- Cost from producing Q units: $10 \times Q$
 - $\Rightarrow$ Profit = Revenue - Costs $\Rightarrow \pi = Q(100 - Q) - 10Q$
- Take derivative of π and set it equal to 0

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 - Demand curve: $P = 100 - Q$
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- Cost from producing Q units: $10 \times Q$
 - $\Rightarrow$ Profit = Revenue - Costs $\Rightarrow \pi = Q(100 - Q) - 10Q$
- Take derivative of π and set it equal to 0
 - $\Rightarrow \frac{d\pi}{dQ} = 90 - 2Q = 0$

Unconstrained Maximization: Example



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- Assumptions:
 - Demand curve: $P = 100 - Q$
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- Take derivative of π and set it equal to 0
 - $\Rightarrow \frac{d\pi}{dQ} = 90 - 2Q = 0 \Rightarrow Q^* = 45$

Unconstrained Maximization: Example



- **Goal:** find a monopoly's profit-maximizing quantity to produce
- Assumptions:
 - Demand curve: $P = 100 - Q$
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- Revenue from selling Q units: $Q \cdot P = Q \cdot (100 - Q)$
- Cost from producing Q units: $10 \times Q$
 - $\Rightarrow$ Profit = Revenue - Costs $\Rightarrow \pi = Q(100 - Q) - 10Q$
- Take derivative of π and set it equal to 0
 - $\Rightarrow \frac{d\pi}{dQ} = 90 - 2Q = 0 \Rightarrow Q^* = 45$
- We will do a more relevant example in Tuesday's class (similar to question on PS1)

Today: The standard model of choice under uncertainty

Next class: Wrap up the standard model (applications), then the evidence against it begins

Remember:

- **Read the syllabus!**
- Problem Set 0 is posted (optional review of optimization) – no need to turn this in
- Problem Set 1 is posted – due Tuesday, September 15